

# Structural Safety Assessment of the Transmission Tower Using Bayesian Network

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**Abstract.** To clarify the disaster-causing factors and preventive measure for the transmission tower, a structural safety assessment method based on Bayesian network is proposed in this study. Firstly, various disaster-causing factors triggering structural damage of transmission towers are systematically analyzed, and three layers network model is constructed based on Bayesian causality. And then, the a priori probability and conditional probability of the network model are quantitatively calculated by combining expert scoring and fuzzy theory. A connectivity tree is formed by building a doxastic map and eliminating elements of the Build Constructive Tree (BuildCT) algorithm. Finally, forward and backward reasoning algorithm using the monitoring data is implemented to capture probabilities of disaster-causing and resulting factors for maintenance. Results shows that the possibility of wind bias tripping is the most feasible factor to be triggered under specific meteorological conditions condition, which is in line with expectation of experts. And strong winds and Serious icing are the key causative factors for tower disconnection and excessive deformation.

**Keywords:** transmission towers; Bayesian networks; connected tree algorithm; conditional probability

## 1. Introduction

Transmission tower is an important type of infrastructure for power transmission, and its safety is directly related to operation of the power system [1]. For example, Typhoon Pigeon attacked the Zhuhai area in China in August 2017, resulting in collapse of a transmission tower at the sea eight A line, so power outages were suffered [2]. Qiqihar strong convective weather in 2020 caused some towers in the 110kV Yalong A and B line collapse, thus power grid was paralyzed in the Longjiang county and mill mountainous areas [3]. Therefore, safety of transmission towers is related to the people's production and life, and has become an important part of the national economic construction.

To grasp the current status of transmission towers, structural safety assessment and timely maintenance is the main way to ensure their safe operation. Currently, the safety assessment mainly relies on static mechanics or reliability analysis, the former is based on the tower structure, and the structural design and analysis is carried out by using the finite element model and static calculation method. The procedure is intuitive and the calculation speed is the biggest advantage of this method.[4] However, many reports [5] pointed out that the safety coefficient of the static analysis is not precise enough, the static calculation result is sometimes unreasonable, and the simplified mode needs to be further studied. Reliability analysis can solve these problems and has become an important method for the safety assessment of transmission tower structures. Yang et al. used the JC method to conduct reliability analysis on transmission tower members under various loading conditions with different load return periods [6]. The reliability index of the pole tower members at a load return period of 100 years is about 27% higher than that of 50 years. Liu et al. Taking a 220kV catenary-type pole tower as a research object, the effect of ice cover thickness and wind speed on the reliability of the structure was investigated [7]. Reliability analysis can address the

effect of different parameters on structural reliability, but it cannot realize the traceability of risk events and the deduction of disaster-causing factors, where it is very important to capture the main factor for maintenance.

Recently, Bayesian Networks provides a new implementation for tracing risk events and inferring causal factors. Zhou et al.[8] proposed a fuzzy comprehensive assessment method for assessing the risk of deep foundation pit construction. This method involves the organization and analysis of the accident database of a deep foundation pit project in Shanghai, allowing for the accurate prediction of the probability of risk events occurring and the determination of the overall risk of the deep foundation pit project. Yu[9] et al. combined the construction simulation technology with Bayesian network, embedded the Bayesian network in the hierarchical simulation model, quantitatively calculated the probability of occurrence of risk events, and realized the Bayesian forward reasoning.

The priori knowledge and sample data should be considered to express the causal relationship in the Bayesian network. However, the way to construct Bayesian network, the priori probability and conditional probability is totally different for various engineering structures, so security assessment of transmission towers based on the Bayesian network need further investigation. To addresses these problems, this study constructs a three-layer Bayesian network for transmission towers, where the intrinsic connection of risk factors is considered. And then a priori probability and conditional probability are deduced on the basic principle of Bayesian network, and finally probability of each risk event and the disaster-causing factor leading to the risk event are solved through the forward and backward reasoning algorithm.

## 2. Bayesian network fundamentals

### 2.1 A priori probability calculation based on fuzzy theory

To address the ambiguity of the root node of Bayesian networks, the triangular fuzzy number is used[10] with the advantages of being simple and easy to compute to integrate the prior knowledge of multiple experts, thus achieving the goal of quantitatively calculating the prior probability of the root node. Very high, high, partial high and medium are used, Partial low, low and very low, there are seven grades, which correspond to the triangular fuzzy number form and the  $\lambda$ -intercept set as shown in Table 1.

Table. 1 Fuzzy language and corresponding triangular fuzzy number form and  $\lambda$  cut set

Number	Fuzzy language	Triangular fuzzy number	$\lambda$ cut set
1	Very low (VL)	$M=(0,0,0.025)$	$M^\lambda=[0,-0.025\lambda+0.025]$
2	Low (L)	$M=(0,0.025,0.05)$	$M^\lambda=[0.025\lambda,-0.025\lambda+0.05]$
3	Partial low (PL)	$M=(0.025,0.0625,0.1)$	$M^\lambda=[0.0375\lambda+0.025,-0.0375\lambda+0.1]$
4	Medium (M)	$M=(0.075,0.1,0.125)$	$M^\lambda=[0.025\lambda+0.075,-0.025\lambda+0.125]$
5	Partial high (PH)	$M=(0.1,0.1375,0.175)$	$M^\lambda=[0.0375\lambda+0.1,-0.0375\lambda+0.175]$
6	High (H)	$M=(0.15,0.175,0.2)$	$M^\lambda=[0.025\lambda+0.15,-0.025\lambda+0.2]$
7	Very high (VH)	$M=(0.175,0.2,0.2)$	$M^\lambda=[0.025\lambda+0.175,0.2]$

In order to obtain the probability of occurrence of the root node  $A_i$ , it is further necessary to transform the fuzzy numbers of the likelihood of occurrence of each causative factor into specific values by defuzzification. Based on Liou's[11] integral value method, the operational properties of the  $\lambda$ -intercept set are considered here to deal with the fuzzy numbers so as to compute the probability of occurrence of each root node.

## 2.2 Calculation of conditional probabilities based on Dempster and Shafer evidence theory (D-S evidence theory).

D-S evidence theory is introduced[12] which utilizes its evidence fusion function to reduce the uncertainty of expert assessment results. Constructing a cognitive judgment matrix that several experts ( $e = 1, 2, \dots, t$ ) are organized to describe the magnitude of the likelihood of occurrence of their corresponding states in the form of numerical ratios based on their own engineering experience and cognitive structure for the elements  $\rho_1, \rho_2, \dots, \rho_r$  in the table of the conditional probabilities to be inferred that need to be defined numerically to construct the cognitive judgement matrices shown in the table 2, respectively.

Table. 2 Cognitive judgment matrix given by expert e

set of elements	$\rho_1$	$\rho_2$	...	$\rho_r$	$\Theta$
$\rho_1$	1	0	...	0	$a_1 p_e$
$\rho_2$	0	1	...	0	$a_2 p_e$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\rho_r$	0	0	...	1	$a_r p_e$
$\Theta$	$1/(a_1 p_e)$	$1/(a_2 p_e)$	...	$1/(a_r p_e)$	1

The eigenvectors corresponding to the largest eigenvalues in the cognitive judgment matrix given by expert e ( $e=1,2,3$ ) are calculated respectively, followed by normalization of the eigenvectors to obtain the basic probability assignments based on expert e's cognition.

## 3. Bayesian Network Construction for Structural Safety Assessment of Transmission Towers

### 3.1 Network modeling

According to the relevant literature[13,14,15,16], it is found that overall overturning of transmission tower (C1), transmission tower disconnection (C2), excessive deformation of transmission tower (C3) and wind bias tripping (C4) are the most dominant types of transmission tower accidents. Combining with the actual experience of the project, we summarize the first-level risk indicators that lead to risk events: material fatigue (B1), bolt loosening (B2), steel corrosion (B3), insufficient structural strength (B4), insufficient structural stiffness (B5), insufficient structural stability (B6). Combining the literature[17], six secondary risk indicators are identified, i.e., the typical disaster-causing factors that cause the transmission tower risk events: strong wind (A1), heavy ice cover (A2), low temperature (A3), humidity effects (A4), initial geometric defects (A5), and node construction errors (A6).

The transmission tower risk factors are analyzed and a Bayesian network topology model is constructed based on the causal relationship between the nodes, as shown in Fig. 1.

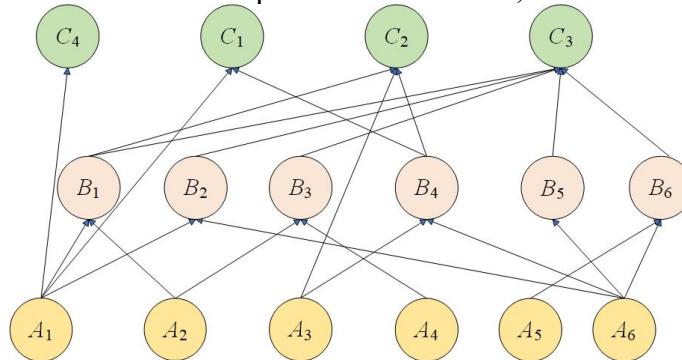


Fig. 1 Bayesian network topology model of temporary stands

### 3.2 A priori probability and conditional probability calculations

#### 3.2.1 A priori probability calculations

Five experts with rich engineering experience in the field of structural design and construction of transmission towers are invited to evaluate the probability of occurrence of root nodes using fuzzy language respectively, and at the same time, the five experts are assigned weight values based on their job titles and engineering experience, which are 0.2, 0.2, 0.3, 0.15, and 0.15, respectively. The results of the expert group's evaluation are shown in Table 3.

Table.3 Expert evaluation results

root node	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
$A_1$	H	H	H	H	PH
$A_2$	H	H	M	PH	PL
$A_3$	L	M	VL	VL	PL
$A_4$	L	VL	VL	VL	VH
$A_5$	PL	L	L	L	PH
$A_6$	PL	L	L	PL	M

In order to further improve the reliability of the assessment results, a weighted average of the Panel's findings was applied to the results, which were expressed as follows.

$$\Gamma_{A_i} = a_1 M_1^\lambda + a_2 M_2^\lambda + \dots + a_j M_j^\lambda \quad (6)$$

Where:  $\Gamma_{A_i}$  is the weighted average  $\lambda$ -intercept set of the root node  $A_i$  assessed by multiple experts,  $i=1, 2, \dots, 11$ ;  $a_j M_j^\lambda$  is the weight of the  $j$ th expert's assessment result and the  $\lambda$ -intercept set of the assessment of the causative factor  $A_i$  respectively. From Section 2.1, each root node  $A_1 \sim A_6$  occurrence probability values, the results are shown in Table 4.

Table. 4 Occurrence probability of risk factors

Hazards	$A_1$	$A_2$	$A_3$	$A_4$	$A_5$	$A_6$
Probability	0.169	0.130	0.012	0.010	0.049	0.049

#### 3.2.2 Calculation of conditional probabilities

Here three experts ( $e=1,2,3$ ) with rich engineering experience in the field of transmission tower structure are organized to give cognitive judgment matrix, and then the DS evidence theory is applied for fusion to obtain the conditional probabilities as shown in Table 5. Based on the above process the conditional probability information of the Bayesian network topology of the complete transmission tower can be calculated, and we have obtained the Bayesian network as shown in Fig. 2.

Table. 5 Conditional probability table of local structure

$A_2$	$A_4$	$P(B_3 A_2A_4)$	
		$Y$	$N$
$Y$	$Y$	0.447	0.553
$Y$	$N$	0.282	0.718
$N$	$Y$	0.229	0.771
$N$	$N$	0.001	0.999

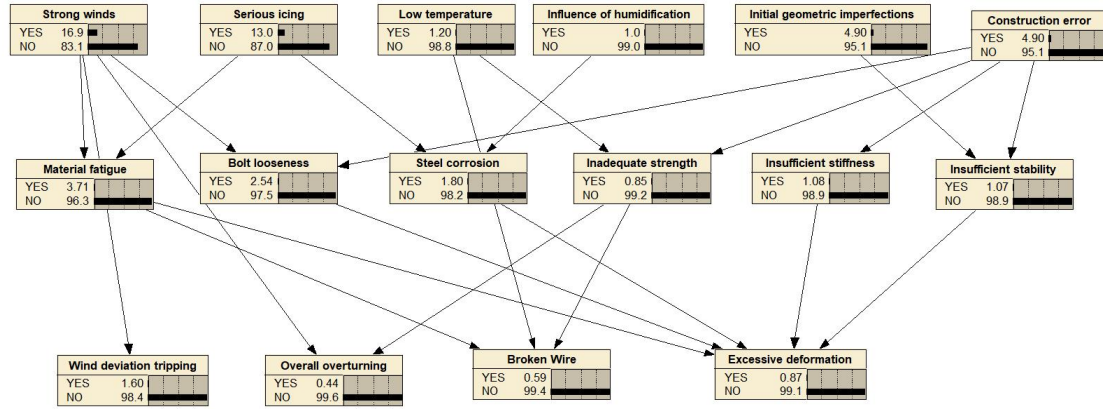
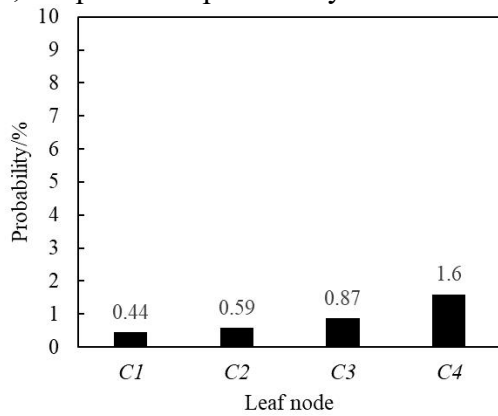


Fig. 2 Bayesian structural network diagram of transmission towers

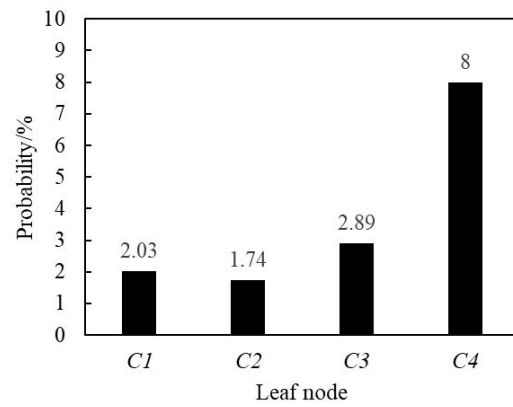
## 4. Analysis of calculation results

### 4.1 Analysis of positive inference results

The purpose of forward reasoning is to predict the probability of occurrence of risky events in the transmission tower structure. The result of calculating the probability prediction of risky events before the use of the transmission tower is shown in Fig. 3(a). The prediction results show that the probability of occurrence of risk events C1, C2, C3 and C4 are 0.44%, 0.59%, 0.87%, and 1.6%, respectively, with C4 (wind deviation tripping) having the highest probability of occurrence. If it has been measured and known that there is A1(strong winds) acting on the transmission tower structure, the predicted probability of occurrence of each risk event is shown in Fig. 3(b).



a) Before use



(b) Known occurrence of A (strong wind)

Fig. 3 Probability prediction of risk events for transmission towers

From the prediction results, it can be seen that when strong wind exists, the probability of occurrence of C4 is 8.0%, i.e. the risk of wind bias tripping is extremely high, which is much higher than the probability of occurrence of overall overturning of the transmission tower, disconnection and excessive deformation. At this time, the relevant operation and maintenance units should be promptly reminded to pay close attention to the structural safety of transmission towers and take precautionary countermeasures.

### 4.2 Analysis of Reverse Reasoning Results

The purpose of backward reasoning is to diagnose the key causal factor that leads to the risk event of the transmission tower structure. The backward reasoning yields the a posteriori probability values of each root node in the case of leaf node occurrence, as shown in Fig. 4.

From the above reasoning results, it can be seen that the key disaster-causing factor leading to the overall overturning of transmission towers (C1) and wind bias tripping (C4) is strong wind (A1),

while the key disaster-causing factor leading to (transmission tower disconnection) (C2) and excessive deformation of transmission towers (C3) is strong winds (A1) and serious icing (A2). Therefore, in order to prevent the occurrence of transmission tower risk events, A1 and A2 should be emphasized.

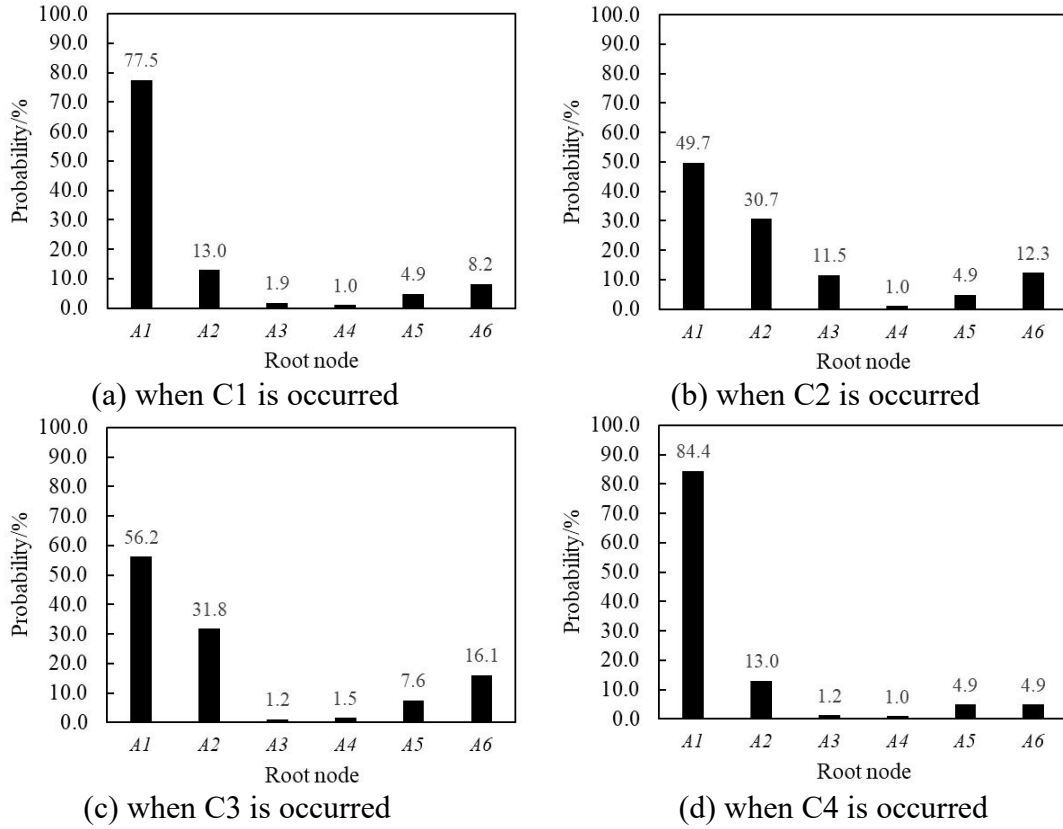


Fig. 4 The posterior probability of each root node

## 5. Conclusion

In this paper, a Bayesian network topology model for structural safety assessment of transmission towers is developed. The probability of occurrence of four kinds of risk events of transmission tower is predicted through forward and backward reasoning of Bayesian network, and the key disaster-causing factors leading to the accidents of transmission tower are identified, which has certain theoretical significance and practical application value. 公式节 (下一节) The conclusions are as follows:

(1) By analyzing transmission tower data and referencing literature, a Bayesian network model was developed to assess tower safety comprehensively, accounting for uncertainties like wind, ice loads, and structural parameters. This model supports decision-making in tower operation and maintenance.

(2) Predictions show wind-induced trips pose the highest risk among tower failures. Countermeasures should prioritize wind-related factors to prevent accidents during tower construction, operation, and maintenance.

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